Business Experience and Start-up Size: Buying More Lottery Tickets Next Time Around?[1]

Alex Coad[+†‡], Julian S Frankish*, Paul Nightingale[+], Richard G Roberts*

*Barclays Bank

+University of Sussex

† Aalborg University, Denmark

‡ RATIO Institute, Stockholm, Sweden

Abstract:
This paper explores the determinants of start-up size by focusing on a cohort of 6247 businesses that started trading in 2004, using a unique dataset on customer records at Barclays Bank. Quantile regressions show that prior business experience is significantly related with start-up size, as are a number of other variables such as age, education and bank account activity. Quantile treatment effects (QTE) estimates show similar results, with the effect of business experience on (log) start-up size being roughly constant across the quantiles. Prior personal business experience leads to an increase in expected start-up size of about 50%. Instrumental variable QTE estimates are even higher, although there are concerns about the validity of the instrument.

Keywords: Start-up size, entrepreneurship, business experience, learning, quantile treatment effects

JEL codes: L26, L25

[1] J.S.F. and R.G.R. write only in a personal capacity and do not seek to represent the views of Barclays Bank. This paper includes references to analyses of Barclays customer records undertaken by the authors with the permission of the bank. All research was conducted in a manner consistent with data protection obligations. No personal details were released to individuals outside of the Barclays Group. We are grateful to Marco Capasso, Gianluca Capone, Giovanni Cerrulli, Alex McKelvie, Francesca Melillo, Puay Tang, Bram Timmermans and Bart Verspagen and seminar participants at INGENIO (Valencia), Universitat Rovira i Virgili (Reus) and the University of Maastricht and the 2012 Schumpeter Conference (Brisbane) for many helpful comments. A.C. gratefully acknowledges financial support from the ESRC, TSB, BIS and NESTA on grants ES/H008705/1 and ES/J008427/1 as part of the IRC distributed projects initiative, as well as from the AHRC as part of the FUSE project. The usual disclaimer applies.

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1. Introduction

A vibrant economy requires new firms to become large enough to compete with incumbents and contribute to economic growth (Geroski, 1995). New firms can become large in two ways – either starting large, or by betting on post-entry growth. The empirical literature has shown that firm growth is notoriously difficult to predict, however (McKelvie and Wiklund, 2010), and that firm growth is best approximated by a random walk process (Geroski, 2000; Coad, 2009). In other words, post-entry growth is very uncertain – but entrepreneurs may be overconfident about their ability to grow after entry (Hayward et al. 2006).[2] In this paper, we focus on the determinants of start-up size. If growth is largely random, then the best way of ensuring that a firm reaches a large size after (say) the first five years of business is if it has a large size to start with.

Unfortunately, start-up size has traditionally been somewhat neglected in the empirical and theoretical literature. Gibrat's Law, for example, ignores a firm's start-up size, and instead assumes that this latter becomes negligible in the limit (see Gibrat, 1931). The model in Jovanovic (1982) assumes that firms enter at the same size. Variations on these models of industrial dynamics, however, have been introduced to incorporate considerations of entry and exit phenomena (Ijiri and Simon, 1977) and size at entry (Levinthal, 1991; Coad et al., 2013).

Although growth is largely random, this is not the case for start-up size, where there are a number of important predictors such as founder characteristics and industry characteristics. Considering that start-up size has a strong influence on post-entry size and survival, researchers might benefit from paying more attention to the determinants of start-up size. Moreover, given that the characteristics of a firm are largely 'imprinted' at the time of founding (Bamford et al., 2004; Geroski et al., 2010), more emphasis on a firm's initial conditions might provide a new and complementary lens for exploring post-entry performance. Understanding the drivers of these effects is not easy because of substantial methodological and data problems. We apply recent developments in quantile econometrics to a high quality dataset to obtain new evidence on the matter.

There is a large and growing empirical literature on the post-entry performance of new firms, whether the focus is on post-entry growth (see e.g. Almus and Nerlinger, 1999; Cabral and Mata, 2003; Lotti et al., 2009; Roberts et al., 2011; Colombo et al., 2012) or post-entry survival (Bates, 1990; Audretsch, 1991; Audretsch and Mahmood, 1995; Acs et al., 2007; Geroski et al., 2010) or even on the time to re-entry in the context of serial entrepreneurship (Amaral et al., 2011). Some studies have even investigated the specific role of start-up size on post-entry survival (Mata et al., 1995; Audretsch et al.. 1999 (a)) or growth (Audretsch et al., 1999 (a,b). In this paper, however, we focus on the determinants of start-up size. In particular, we focus on the effect of prior entrepreneurial experience on start-up size. Recent theoretical work in the entrepreneurship literature has suggested that entrepreneurial learning is a key variable for new business performance (survival and growth). However, empirical work often finds no evidence of entrepreneurial experience influencing observed post-entry performance (Metzger, 2006; Frankish et al., 2013; Nielsen and Sarasvathy, 2011; Gottschalk et al., 2013), or else it finds that the benefits of entrepreneurial experience only have a marginally significant impact on economic performance (Gimeno et al., 1997). There are a number of reasons why there might be no scope for learning in entrepreneurial contexts: business experiences may be too dissimilar to allow for repetition-based learning, especially when we consider that

[2] According to the 'Hubris theory of Entrepreneurship,' Proposition 5 in Hayward et al. (2006, p167) posits that: "More overconfident founders start their ventures with smaller resource endowments and this increases the likelihood that their ventures will fail."

entrepreneurs are prone to overoptimism and overconfidence (Frankish et al., 2013). Indeed, if as is argued in the literature, firm growth is best approximated by a random walk (Gibrat, 1931; Levinthal, 1991; Geroski, 2000), there is no scope for learning in the context of random processes by definition.

However, if we accept that sales growth is largely random, there may still be a role for entrepreneurial experience to enhance survival. This could occur if entrepreneurial experience leads entrepreneurs to 'learn' to start with a larger start-up size, even if they have little control over post-entry performance. Indeed, experienced entrepreneurs may have better networks and access to knowledge and information, enabling them to assemble more resources at start-up. The analogy would be that an individual will last for longer at a gambling table if they arrive at the table with a larger pile of gambling chips – although the game is random, they have boosted their chances of survival (Storey, 2011). Put differently, one can increase one's chances of winning the lottery – even if we acknowledge that this is a game of chance – if one entered the game with more lottery tickets. Therefore, we suggest that the finding of higher survival for experienced entrepreneurs that has been observed in previous work (Klepper and Sleeper, 2005; Buenstorf and Klepper, 2009) can be reunited with a random walk model of post-entry performance – if entrepreneurs are able to start again larger.[3] This is a plausible explanation given the previous findings that start-up size enhances survival (Audretsch, 1995, Coad et al., 2013; but see also Audretsch et al, 1999a).

In this paper, we contribute to the literature in a number of ways. First, we are the first to focus explicitly on the link between business experience and start-up size. This is important because of policy interest in encouraging entrepreneurs to start again after failure, as well as interest in the potential role of entrepreneurial learning and experience on business performance. It is also important because a large start-up size is arguably the best predictor of survival and post-entry size, given that post-entry growth is so difficult to predict. Start-up size is therefore a leading indicator of start-up quality, and this study seeks to advance research on start-up size. Second, we present new evidence from a rich dataset that includes novel variables such as business experience, sources of advice, and bank account activity (such as turnover volatility and use of overdraft). In particular, our ability to accurately measure start-up size in terms of turnover (while all previous comparable analyses have focused on employment) allows us to explore for the first time the determinants of start-up size at the lower quantiles of the start-up size distribution. Third, we apply new econometric techniques (quantile treatment effects (QTE) and instrumental variables QTE) as we attempt to obtain improved estimates of the determinants of start-up size.

Section 2 surveys the previous empirical literature on the determinants of start-up size. Section 3 formulates our hypotheses. Section 4 presents the methodology. Section 5 describes our data, while Section 6 contains the analysis. Section 7 concludes.

2. Related Literature

The previous literature on the determinants of start-up size is surveyed in Table 1. Some studies explain start-up size in terms of entrepreneur characteristics, such as education, skills, and work experience (e.g. Barkham, 1994; Mata, 1996, Astebro and Bernhardt, 2005). Other studies have focused more on industry-level characteristics, finding that start-up size is positively associated with variables such as turbulence, minimum efficient scale (MES), and industry growth (Mata and Machado, 1996; Gorg et al., 2000; Arauza-Carod and Segarra-Blasco, 2005). We seek to complement

[3] Note that this is not the usual meaning of the word 'entrepreneurial learning.' In our model, entrepreneurs do not apply their learning to improve their post-entry performance, but instead they 'learn' to increase their chances of success by starting large - all the while recognizing that they are playing a random game.

this stream of literature by applying an improved methodology to an unusually rich dataset that includes new variables. In particular, we focus on the relationship between business experience and start-up size, controlling for a number of other possible influences.

Table 1 highlights some differences between studies in terms of regression methodology. While some early contributions (Barkham, 1994; Mata, 1996) used standard OLS regressions to obtain results relating to the average start-up size, subsequent studies, beginning with Machado and Mata (1996), apply quantile regression to explore heterogeneous effects across the start-up size distribution. Quantile regression is a useful tool for this context: indeed, the prototypical application of quantile regression is the analysis of birthweight (Koenker and Hallock, 2001) which has conceptual parallels with firm start-up size. Given that firms display considerable heterogeneity in their start-up sizes, and that different factors matter for firms of different sizes, quantile regression is a useful tool for exploring this heterogeneity.

A number of caveats affecting previous studies can also be mentioned. First, it is somewhat perplexing that these studies do not really have detailed information on start-up size. They focus on businesses above a certain size threshold (e.g. 1+ employees, 3+ employees, or even 5+ employees) which means that if a firm starts below this threshold but grows above it, it will mistakenly be classified as a new start-up even if it is already several years old. For example, Nurmi (2006: p41) writes openly that "these plants may have existed before the first observation with less than three employees." However, as discussed below, we have precise information on firms at start-up.

Second, previous work has measured start-up size almost exclusively in terms of employment,[4] which is a problem because many firms start with the lowest (threshold) value of number of employees, and there is insufficient variation at the low quantiles to provide meaningful results. In our paper we use an alternative indicator of start-up size, namely log of annual turnover in the first year. As Table 1 shows, our paper is the only paper to investigate what happens at the low quantiles (that is, the 10% quantile). Other papers start their analysis at the 15%, or even the 20% quantile in the case of Girma et al. (2010). Furthermore, if the analysis includes small businesses with 1+ employees (as opposed to thresholds of 3+ or 5+ employees) then the high frequency of firms with exactly 1 employee (due to the integer constraint affecting employee headcounts) is problematic for computation of a quantile regression solution (see e.g. Gorg et al. 2000, their Table 6), where the coefficient estimates are tiny, and t-statistics and significance levels are missing).

Third, previous work has been somewhat limited in terms of the explanatory variables available. We complement previous work by investigating the influence of novel explanatory variables, in countries that have escaped prior analysis (i.e. England and Wales).

The prior literature has suggested that future work could fruitfully investigate the role of financial factors on firm size. Nurmi (2006: p57) writes that: "In the further analysis, the effect of financial constraints on entry scale would be worth studying." (see also similar recommendations from Colombo et al. (2004)). Previous work has also shown interest in investigating prior business

[4] Da Rin et al. (2010) measure entry size as the median total assets at the country-industry level, but do not apply quantile analysis.

experience (e.g. Capelleras and Hoxha (2010, p423) who write that "a natural extension of the present analysis is to include differing types of prior experience of entrepreneurs.") We are in a position to address this gap in the literature.

Table 1: Related literature.

Reference	Estimator	Quantiles	Dep. Var.	Indep. Var.	Data	Lower limit
Barkham (1994)	OLS	n/a	Log turnover, assets, empl.	No. founders, education, skill, growth motivation,	Survey of accountants on 304 UK firms, 1976-1986	None specified
			measured over first 3 yrs.	sector, region		
Mata (1996)	OLS	n/a	Log(Empl)	Entrepreneur and Industry characteristics	1079 Portuguese firms	5+ employees
Mata and Machado (1996)	QR	15, 25, 50, 75, 90	Log(Empl)	Industry characteristics	766 Portuguese firms	5+ employees
Gorg et al. (2000)	QR	15, 25, 50, 75, 90	Log(Empl)	Industry characteristics	Ireland, national records	1+ employees
Colombo et al. (2004)	OLS	n/a	Log(Empl)	Human capital, finance, industry characteristics	391 Italian tech firms	1+ founders/employees
Astebro and Bernhardt (2005)	2SLS	n/a	Log(Capital)	Entrepreneurial ability, human capital, financial wealth	1987 US CBO survey data, white males	$500+ in sales
Arauza-Carod and Segarra-Blasco (2005)	QR	15, 25, 50, 75, 90	Log(Empl)	Industry-level: growth, margins, exit rate, entry barriers	Spanish manufacturing, 1990-96, 32997 obs	3+ employees
Colombo and Grilli (2005)	OLS	n/a	Log(Empl)	Human capital, finance, industry characteristics	391 Italian tech firms	1+ founders/employees
Nurmi (2006)	QR	15, 25, 50, 75, 90	Log(Empl)	Industry and region characteristics	69322 observations on Finnish plants, 1989-2000.	3+ employees
Resende (2007)	QR	15, 25, 50, 75, 90	Employees	Industry characteristics	15673 Brazilian plants in 1997.	5+ employees
Capelleras and Hoxha (2010)	OLS	n/a	Log(Empl)	Founder characteristics	Interviews with 555 founders, Kosova	1+ employees
Da Rin et al. (2010)	FE, GMM	n/a	Capital size	Tax rate, measures of the political process	39 industries, 17 countries, 1997-2004	Year after incorporation
Girma et al. (2010)	QR	20, 25, 50, 75, 90	Log(Empl)	Grant receipt, foreign status, and industry characteristics	11475 observations on Irish plants, 1972-2000.	1+ employees
Hvide and Moen (2010, Table 2)	OLS	n/a	Log of equity, assets,	Wealth, wage, age, education	1307 Norwegian startups	Incorporated, NOK500'000
			employees, debt			sales and 2+ employees
Melillo et al. (2012)	ZINB	n/a	Employees	Entry mode, human capital, labour mkt experience	18058 obs, Swedish knowledge intensive sector	1+ employees
This paper	(IV) QTE	10, 25, 50, 75, 90	Log(Sales)	Entrepreneur, bank account and industry characteristics	Cohort of 6247 UK startups, 2004.	None

Notes: OLS refers to Ordinary Least Squares regression; QR - Quantile Regression; FE - Fixed-Effects panel OLS; GMM - dynamic panel data GMM; 2SLS - two-stage least squares; ZINB - Zero-Inflated Negative Binomial; IVQTE - Instrumental Variable Quantile Treatment Effects. Barkham (1994) does not specify that he uses OLS, but this seems to be the most likely case.

3. Theory

3.1 Start-up size, growth and survival

In this section, we present a simplistic model of firm dynamics that (despite its drawbacks) has the advantage of yielding clear predictions of the relationship between start-up size, growth and survival. In the following model, growth is characterized as a random walk process following Levinthal (1991) and Coad et al. (2013). This is done in recognition of the fact that, although there are some factors that are systematically associated with growth rates (such as size and age), nonetheless these factors only explain a small share of the variation in growth rates, and do not go very far in predicting how much firms will grow (McKelvie and Wiklund, 2010), leading scholars to suggest that firm growth is best modeled as a random walk (Geroski, 2000; Coad, 2009).

Size in the current period depends on size in the previous period, plus a random shock. Let firm size at time t be measured in terms of its capital K_t, and let start-up size be denoted as K_0. Firm size evolves as a random walk, with $K_t = K_{t-1} + \varepsilon_t$, where ε_t follows a Gaussian distribution with mean μ and variance σ^2. When $\mu = 0$, we have a pure random walk, whereas when $\mu > 0$ then there is a steady increase in expected capital stock over time. According to the Gambler's Ruin model, firms are assumed to exit when their size (proxied by stock of capital) reaches zero. The analogy is that of a gambler who leaves the gambling table when they have run out of gambling chips. The time taken until the firm first reaches the bankruptcy condition $K_t = 0$ can be expressed as the cumulative distribution function of a random variable in the following way (known as the Bachelier-Levy formula):

$$F(t \mid K_0, \mu, \sigma) = N\left(-\frac{\mu t + K_0}{\sigma\sqrt{t}}\right) + e^{-2K_0\frac{\mu}{\sigma^2}} \cdot N\left(\frac{\mu t - K_0}{\sigma\sqrt{t}}\right) \qquad (1)$$

where N(.) represents the cumulative density of the standard normal distribution. Time to exit is thus a function of three parameters: the trend in the random walk μ, the variance σ^2 of the growth shocks, and start-up size K_0. Even though growth may be a random process, the expected survival time can be increased by raising the size at start-up K_0.

Having considered the relationship between start-up size, growth and survival, it becomes clear that entrepreneurs may seek to enhance the survival of their ventures by influencing their start-up size, even if they have no control over post-entry growth (which is approximated here by a random process). We now formulate some hypotheses regarding how start-up size can be influenced by business experience.

3.2 Hypotheses derivation

We hypothesize that business experience is associated with a larger start-up size, as entrepreneurs become more aware of the survival benefits of starting large, and also because experienced entrepreneurs are better positioned to assemble the knowledge, social capital, and other resources that they will use at start-up (Davidsson and Honig, 2003). In their analysis of Asian-owned businesses in the US, Robb and Fairlie (2009, p841) observe that "the amount of start-up capital used in the business has a strong positive association with all of the business outcomes." Experienced entrepreneurs may be better able to convince investors of their ideas, be more skilled in selecting ideas, be better positioned in existing business networks (higher social capital due to more contacts and stronger links), and be better able to assemble resources and assets at the time of start-up to build on business opportunities.

Hypothesis 1: business experience leads to higher start-up size on average

These advantages of experience will not be evenly distributed however. Prior business experience may enable some entrepreneurs to obtain valuable experience, build a reputation, convince others of their entrepreneurial skills, as well as accumulate their own resources that they may then reinvest in their subsequent business. Hence in some cases, prior business experience will enable some entrepreneurs to start their subsequent business venture at a very large scale. We expect that at the upper end of the start-up size distribution, these advantages will be magnified:

Hypothesis 2a: business experience leads to higher start-up size at the upper quantiles

While some entrepreneurs may start their business in response to exciting new market opportunities, other 'necessity' entrepreneurs may start a new business out of lack of other labour market alternatives.[5] Less successful entrepreneurs may be disappointed with their previous poor performance, but they may nonetheless choose to continue in the self-employed lifestyle for personal reasons. Therefore, to minimize their losses, or perhaps because they have difficulties in attracting capital, they might start again at a smaller scale. This is more likely to be the case for those businesses at the lower end of the start-up size distribution. Although such firms may have a lower value of K_0, they may also seek to manipulate σ by taking few risks, and persisting at a small scale.

Marlow et al. (2011) undertake interviews and report that some entrepreneurs that previously failed would choose a smaller scale for their subsequent start-up, despite their prior business experience. This is presumably because they are more cautious and less confident of their abilities. One such entrepreneur is quoted as saying: "We started a phoenix company doing exactly the same but on a much smaller scale" (Marlow et al., 2011, page 5). Relatedly, Wright and Stigliani (2013) consider that "habitual entrepreneurs that have failed previously may become more risk-averse in their next venture" (p10), which may lead to a smaller subsequent start-up size. Therefore we posit:

[5] This could be the case of those 'necessity entrepreneurs' who enter self-employment after a spell in unemployment (see e.g. Thurik, 2003; Andersson and Wadensjo, 2007; Santarelli et al., 2009; Caliendo and Kritikos, 2010).

Hypothesis 2b: business experience leads to lower start-up size at the lower quantiles

4. Methodology

In our analysis of start-up size, we are interested in going beyond the 'average effect on the average firm' to explore the full distribution of start-up size. Since conventional regression estimators (such as OLS) are of limited use, we use the more appropriate quantile methods, beginning with quantile regression (Section 6.1).

However, it is often forgotten that quantile regression is a linear estimator (Koenker and Hallock, 2001, see in particular their Figure 3). Quantile regression therefore suffers from the limitations of the linearity assumption. This leads to problems of over-smoothing – problems of extrapolation, interpolation, and off-support inference. It may be that quantile regression estimates come from comparing firms that are not truly comparable. Instead, we make use of developments in quantile treatment effects (Firpo, 2007), extended to the case of instrumental variables (IV) estimation (Abadie et al., 2002; Frolich and Melly, 2008; 2010). Treatment effects (estimated using matching techniques) and instrumental variables are both techniques that seek to yield causal inference rather than just reporting mere associations – we start by focusing on treatment effects (Section 6.2) before combining these two techniques in our application of Instrumental Variables Quantile Treatment Effects (IVQTE) presented in Section 6.3.

A number of previous studies of the determinants of start-up size, reviewed in Table 1, have considered the issue of a minimum start-up size, below which firms do not enter (and which therefore leads to selection bias). Mata (1996) and Colombo et al. (2004, p1190) write that they only observe those firms that were actually founded, not those that were interested in founding but were below the minimum start-up size threshold, and so they consider that they have a latent variable setup. In our dataset, we observe a wide spectrum of firm start-up sizes, even those that were founded and operate at a very small scale. We have 6247 firms at start, but only 5192 survive the first year. Of the 5192 businesses that survived the first year, the minimum start-up size was a firm that made only £31 in turnover (i.e. less than $1USD a week). Because of our detailed coverage of micro businesses, we do not apply this latent variable framework.

5. Data

Our data are taken from the customer records from Barclays Bank. Barclays Bank provides the primary current (checking) account facility for just over 20% of all businesses in England & Wales with turnover of less than £1 million. Their active customer base in this market is in excess of 500,000 firms. Firms in our dataset are present in all sectors (with the exception of the financial services sector).

Bank data constitutes a novel and promising source of information on start-up size. First, we can accurately observe the exact date of start-up. We focus on a cohort of new firms that were started

between April and June 2004. Only those firms with trading activity over the period April-June 2004 are included, and so dormant businesses are excluded. Other studies based on administrative data suffer from the problem of only observing new firms once they exceed a certain size threshold.[6]

Second, our measure of start-up size is a measure of firm sales (to be precise, we look at credit turnover which corresponds to the value of payments into the business current account). We therefore use a continuous variable that doesn't suffer from problems related to indivisibilities. Unlike data on turnover, employment headcounts are subject to integer constraints that are especially problematic for quantile regression estimation at the lower quantiles. However, the vast majority of previous investigations of the determinants of start-up size, surveyed in Table 1, focus on start-up size as measured in terms of number of employees. A potential shortcoming of using turnover, however, could be that, for new ventures, sales take some time to materialize – although we argue that our analysis is at least a useful complement to the existing literature. Furthermore, we also take number of owners as an alternative indicator of start-up size in our multivariate regressions.

Third, our data is accurate and boasts comprehensive coverage of all new firms. Administrative datasets (based on VAT records or tax returns) are prone to suffer from inaccuracies, whether they are due to accidental misreporting or deliberate tax evasion. Survey datasets have similar problems of inaccurate data as well as also suffering from questionable representativeness of the full population of start-ups. In our data, both the bank and the entrepreneurs have strong incentives to ensure that the data is accurate and timely. Moreover, the bank is able to accurately gather information on the customer's activity by overseeing the customer's account.

It is important to understand that the creation of a business bank account is NOT conditional on any other banking service such as a deposit account, an overdraft facility or a term loan. It is therefore NOT a sample of bank borrowers, but instead a sample of all new business bank customers. However, we also include information on the existence and use of an overdraft facility for each customer as supplementary explanatory variables in our regressions. As part of the opening of account facilities new business owners were asked to complete a voluntary questionnaire relating to their prior employment and educational attainment, together with some personal details such as age and gender, as well as information on the sources of advice or support approached prior to start-up. The response rate for this initial questionnaire was close to 100%, as might be expected.

We can also identify which firms switch bank to use an account at a different bank. These 'switchers' are identified and removed from our analysis. Furthermore, the UK, unlike many countries in continental Europe, is not characterized by multiple banking (Ongena and Smith, 2000), and so the account at a single bank is therefore likely to capture the full trading activities of the new venture.

Our outcome variable of interest relates to the start-up size of the new venture (measured initially as the natural logarithm of annual credit turnover, in GBP). However, we can expect that different sectors are characterized by different Minimum Efficient Scales (MES), due to industry-specific characteristics relating to entry barriers, sunk costs, industry-specific technological factors, and so

[6] For example, in the UK, the threshold for Value Added Tax (VAT) registration was set at a turnover of GBP 73,000 for the 12 months from 1 April 2011. Firms below this threshold are not required to register.

on.[7] To take this into account, our dependent variable for the econometric analysis in Section 6 is relative start-up size, which is normalized relative to the sector's MES (where this latter is proxied by median start-up size for all firms in the same cohort in that sector). Our dependent variable, relative start-up size, is therefore measured as the natural logarithm of turnover in the first year minus the natural logarithm of the median turnover in the first year for all firms in that sector. An alternative approach for taking sector-specific MES into consideration would be to repeat the analysis one sector at a time, but due to small numbers of observations in several sectors we eventually decided against this approach.

Our main independent variable is a dummy variable corresponding to prior business experience of the individual (which will be instrumented in our IV QTE analysis by a dummy variable capturing the prior business experience of the individual's parents). To control for the potentially confounding effects of other variables and to alleviate omitted variable bias, we include a series of other variables as controls. Our dataset includes information on the founder: age, gender, education (4 dummies corresponding to none; GCSE; A-level; and Degree or higher), as well as the sources of advice approached at the time of start-up. We also have information at the level of the new business: number of owners, legal form, industry dummies and region dummies (although we need not include time dummies).[8] A novel feature of this dataset is the information on the bank account activity of the new venture – that is, turnover volatility, use of authorized overdraft facility (use and extent of use), and also unauthorized use of an overdraft facility (use and extent of use). Our variables are described in more detail in Table A1 in the Appendix.

This dataset allows us to address some of the limitations and constraints of previous work. For example, Colombo and Grilli (2005, page 245) highlight that "due to the survey-based nature of the dataset, we do not have information on firms that entered the market but failed and exited before the survey date." This is not a problem with this dataset, as it captures firms that do not survive their first year. So while there are 6247 firms at the start, only 5192 survive the first year.[9] This is important because as Colombo and Grilli (2005 page 246 fn 4) note "there may be a systematic correlation between the age of sample firms and their start-up size." The ability to capture data on nascent businesses is important as it can lead to substantial problems of bias. This has recently been highlighted by Bamford et al. 2004 (see Table 1), who observe that many studies of new firms actually use data on firms that may be up to 18 years old(!). This is part of a more general problem highlighted by Nurmi (2006) that limits previous work that captures data starting from the time when firms cross the lower size threshold. This is not a problem with our data.

Summary statistics on the distribution of start-up size are presented in Table 2. With regards to the start-up size distribution, the null hypothesis of log-normality is rejected.[10]

[7] We are grateful to a reviewer for bringing this to our attention.

[8] Since we are analyzing a cross-section of data corresponding to the first year of a cohort of firms that start in the same quarter, there is no variation in time period, and hence there is no need to include year dummies.

[9] We can infer the start-up size of those firms that do not survive their first year by taking the number of owners as a proxy for startup size. Following Colombo et al. (2004, p1192), we have information on number of owners at start-up for 1053 businesses that do not survive their first year (76.5% of which have just one owner) and 5176 businesses that do survive their first year (71.5% have just one owner). On this basis, it seems that there are no major differences in size between those businesses that exit before the end of the first year, and those that survive.

[10] A Skewness-Kurtosis test of normality returns a p-value of 5.63E-13.

Correlation coefficients in Table 3 show that start-up size is highly correlated with size in later years, which suggests that firms that have a large start-up size are likely to remain large, probably larger than those who enter small and aspire towards post-entry growth.

Table 2: summary statistics for start-up size (i.e., log of turnover in the first year). 5192 observations.

	Mean	SD	Skewness	Kurtosis	Min	10%	25%	Median	75%	90%	Max
turnover	116724.1	529335.8	44.07407	2547.075	31	5734	15108	39276	105339	261042	32000000
log(turnover)	10.55343	1.494644	-0.18581	3.495806	3.433987	8.654169	9.622946	10.57836	11.56493	12.47244	17.28011

Table 3: Correlation coefficients (Pearson and Spearman rank) of start-up size with size in subsequent years. Size measured in terms of log of annual turnover.

	year 2	year 3	year 4	year 5	year 6
Pearson correlation	0.8352	0.7513	0.7093	0.6815	0.6687
Rank correlation	0.8641	0.7910	0.7510	0.7286	0.7053
No. Obs.	3878	3092	2575	2184	1867

Figure 1 shows the evolution of the firm size distribution for the subset of firms surviving 6 years, providing further evidence of the stability of the firm size distribution in the first few years after entry.

Figure 2 (left) shows the firm size distribution, distinguishing between firms according to the business experience of the founder. Figure 2 (right) shows that founders with prior business experience have firms that are larger across the firm size distribution.

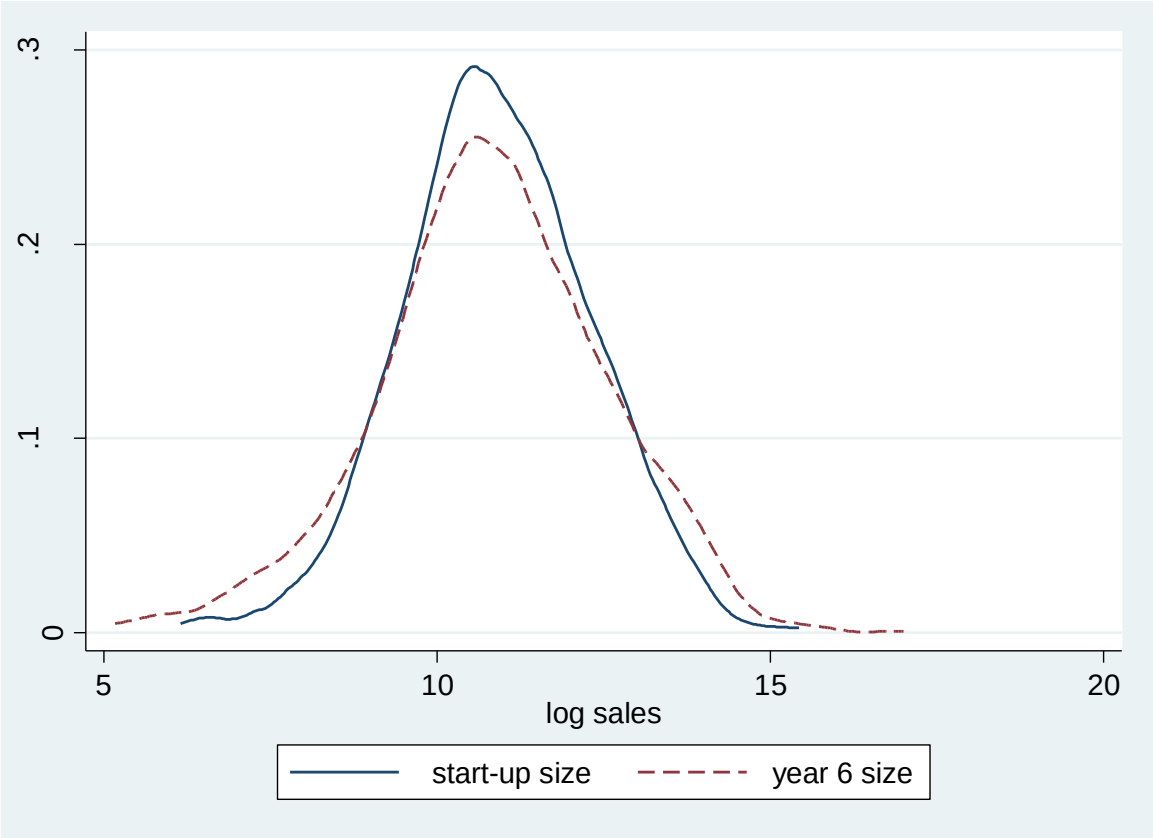

Figure 1: evolution of the firm size distribution for the subset of firms surviving 6 years. Epanechnikov kernel.

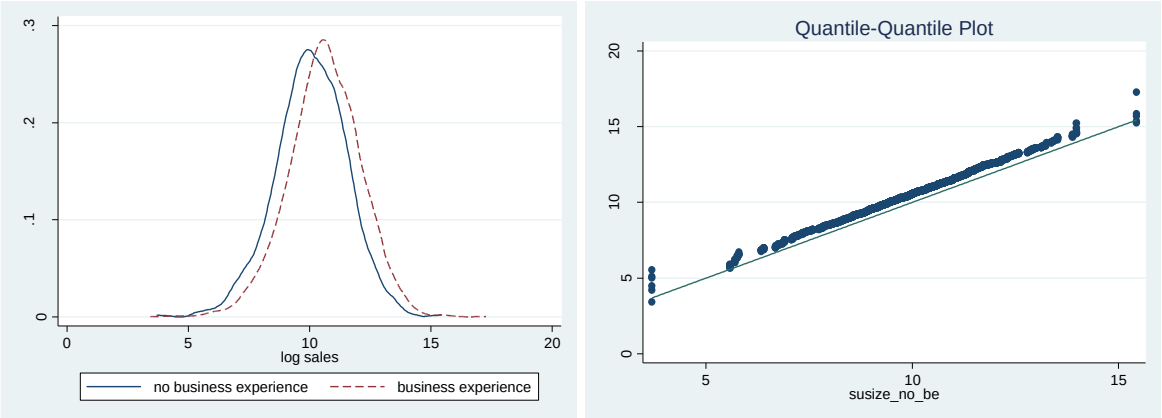

Figure 2: left: start-up size distribution for firms, depending on whether the founder has prior experience running a business (either personal experience or parental experience). Epanechnikov kernel. Right: quantile-quantile plot showing the distribution of start-up size for individuals with prior business experience (either personal or parental) in comparison to that for those without business experience.

6. Analysis

6.1 Quantile regressions

Table 4 contains our regression results, where the dependent veriable is relative start-up size, although in column (4) our dependent variable is number of owners (following Colombo et al. 2004, p1192).[11] Our main result is that prior business experience has a positive impact on start-up size, which offers support for Hypothesis 1. This result emerges from OLS, Poisson, and quantile regression estimates, which suggests that it is a robust finding. The estimated coefficient displays no monotonic trend across the quantiles,[12] and takes values between 0.268 and 0.411, which is roughly in line with the estimates in Astebro and Bernhardt (2005, their Table II). The fact that the proportionate increase in start-up size stays roughly constant across the quantiles implies that the absolute amount (in £) increase in start-up size associated with prior business experience increases – hence providing nuanced support to hypothesis 2a (i.e. roughly constant *proportion* but increasing *amount*). Nonetheless, we reject hypothesis 2b, because business experience has a significant *positive* (rather than negative) effect on start-up size even at the lowest quantiles. This could be because, even at the lower quantiles, business experience confers a number of advantages (such as social capital, knowledge capital, access to resources) that offset the desire to operate at a small scale. It could also be a feature of our revenue-based indicator of start-up size, which might yield different results compared to the situation where start-up size was measured in terms of inputs such as employees or total fixed assets (e.g. discouraged entrepreneurs may seek to maximize revenue while keeping their investments low).

Parental business experience usually has a positive effect on start-up size, even when controlling for personal business experience. Parental business experience could have a positive effect on start-up size over and above the effect of personal business experience though channels such as parental support, better access to financing, better positioning in business networks, and so on.

Although our main focus is on the role of business experience on start-up size, it is also worth briefly discussing the results obtained for the other variables. Age has an inverse-U-shaped effect on start-up size that becomes slightly more positive for the largest business starts. Education also plays a role in start-up size. The dummy corresponding to the highest education level (degree or above) is always highly significant in all regressions, and shows no clear trend across the quantiles. The second highest education dummy (A-level) is significant in some cases, such as being a factor associated with the number of owners at start-up (Column (4)). This is an interesting complement to previous findings on Barclay's data that finds no effect of education on survival or growth (Coad et al., 2013). Education may have no impact on survival if both start-up size and the exit threshold (corresponding to outside

[11] The variable 'number of owners' has mean 1.320, standard deviation 0.573, minimum = 1 and maximum = 6, for 6229 observations in the first year.

[12] Further analysis, available from the authors upon request, shows that the effects of prior business experience (both personal and parental) show no clear trend over the quantiles (neither increasing nor decreasing).

options) are correlated (Gimeno et al., 1997). Furthermore, education will not affect growth rates if growth is essentially a random walk process.

Sources of advice are often significant but are not all of the same sign – the association with start-up size is sometimes positive and sometimes negative. The positive effect of accountant and solicitor advice increases over the quantiles. Some sources of advice have effects on start-up size (controlling for other factors such as education and age) that, if significant, are always negative (for example Enterprise Agency/Business Link, College, and Family), which suggests that entrepreneurs may sometimes be encouraged to enter prematurely at a smaller scale. We also interacted education with sources of advice (in anticipation that education augments the founder's capacity to integrate external advice), but this did not yield any particularly striking results (results are available from the authors).

Our bank account variables have not been considered in previous investigations of start-up size and are, in themselves, a contribution to the literature. These variables are measured over the course of the firm's first year, and are therefore measured simultaneously to our dependent variable, and so our coefficient estimates for these variables should not be seen as causal effects, but rather as associations.[13] Inclusion of these variables is associated with a jump in R2 from 0.087 to 0.277 (compare columns (1) and (2)), which indicates that these variables (although endogenous) offer valuable insights into the factors associated with start-up size. Inclusion of these variables also decreases the effect of prior business experience on start-up size, which suggests that business experience may increase start-up size via causal channels such as availability and use of banking facilities (such as authorized overdrafts) and perhaps smoothing of income streams (that is, to reduce volatility). With regards to these variables, we observe a number of significant effects. Volatility of monthly turnover is negatively associated with start-up size, especially for smaller start-ups (at the lower end of the distribution) – presumably because those less fortunate firms with a smaller start-up size face an erratic cash flow instead of a steady stream of income. The availability of an (authorized) overdraft facility is positively associated with start-up size, although the extent of the use of the authorized overdraft is negatively associated with start-up size, especially for larger start-up sizes (at the upper quantiles).[14] The extent of use of an *un*authorized overdraft is strongly negatively associated with start-up size across the quantiles, which suggests that entrepreneurs that engage in this kind of risky financial behavior (which is expensive and bordering on the penal) may be facing extreme financial difficulties such as a cash-flow that is far below expectations.

Finally, we observe that number of owners has a large positive effect on start-up size, presumably because a larger number of owners can manage a larger scale of operations. Male owners are also positively associated with a larger start-up size.

[13] When we repeated the estimations in Table 4 excluding these bank account variables, our results were similar to those obtained previously.

[14] These contrasting results for availability and use of overdraft can be compared to findings in Colombo and Grilli (2005, their Table 2) that bank debt is not significantly associated with start-up size.

Table 4: OLS, poisson, and quantile regression results for the determinants of relative start-up size. OLS and Poisson estimates from robust standard errors (Huber/White/sandwich estimator). Quantile regression standard errors (and hence t-statistics) are bootstrapped, using 250 replications. Robust standard errors in parentheses. Key to significance levels: *** p<0.01; ** p<0.05; * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	**susize_rel**	**susize_rel**	**susize_rel**	**susize_rel**	**susize_rel**	**susize_rel**	**susize_rel**	**susize_rel**	**susize_rel**
	OLS	**OLS**	**OLS**	**Poisson**	**10% QR**	**25% QR**	**median QR**	**75% QR**	**90% QR**
Parental business exp.	0.106***	0.0929**	0.0890**	0.0147	0.0635	0.0551	0.131***	0.0657	0.120**
	(0.0409)	(0.0365)	(0.0354)	(0.0127)	(0.0578)	(0.0440)	(0.0437)	(0.0535)	(0.0570)
Self business exp.	0.510***	0.419***	0.332***	0.0812***	0.328***	0.268***	0.312***	0.411***	0.349***
	(0.0455)	(0.0408)	(0.0404)	(0.0134)	(0.0645)	(0.0481)	(0.0476)	(0.0594)	(0.0668)
age	0.0137***	0.0111***	0.00897***	0.00425***	-0.00150	0.00645***	0.00959***	0.0151***	0.0137***
	(0.00224)	(0.00203)	(0.00198)	(0.000628)	(0.00308)	(0.00222)	(0.00235)	(0.00263)	(0.00334)
age_squared	-0.00125***	-0.00107***	-0.000859***	-0.000343***	-0.000808***	-0.000795***	-0.00101***	-0.000849***	-0.000600**
	(0.000167)	(0.000149)	(0.000148)	(4.40e-05)	(0.000221)	(0.000159)	(0.000170)	(0.000204)	(0.000299)
Education dummies									
GCSE	0.0564	0.0350	0.0315	0.0287*	0.0324	0.0627	0.0537	0.0906	0.00278
	(0.0520)	(0.0469)	(0.0463)	(0.0163)	(0.0781)	(0.0547)	(0.0578)	(0.0644)	(0.0851)
A-level	0.147**	0.218***	0.133**	0.0574***	0.132	0.171**	0.111*	0.148*	0.109
	(0.0631)	(0.0564)	(0.0539)	(0.0199)	(0.0960)	(0.0671)	(0.0651)	(0.0849)	(0.0923)
Degree or higher	0.231***	0.399***	0.217***	0.124***	0.300***	0.302***	0.184***	0.259***	0.242**
	(0.0559)	(0.0507)	(0.0512)	(0.0181)	(0.0822)	(0.0609)	(0.0589)	(0.0696)	(0.106)
Sources of advice									
EABL	-0.396***	-0.320***	-0.268***	0.00691	-0.177*	-0.180***	-0.290***	-0.280***	-0.286***
	(0.0650)	(0.0569)	(0.0555)	(0.0209)	(0.103)	(0.0656)	(0.0675)	(0.0694)	(0.0988)
Accountant	0.316***	0.236***	0.0880**	0.0449***	-0.00373	0.0792	0.144***	0.113**	0.0643
	(0.0419)	(0.0374)	(0.0371)	(0.0135)	(0.0630)	(0.0485)	(0.0428)	(0.0506)	(0.0684)
Solicitor	0.286***	0.273***	0.169*	0.0946***	0.175	-0.0211	0.158	0.293**	0.351**
	(0.102)	(0.0923)	(0.0920)	(0.0306)	(0.151)	(0.121)	(0.112)	(0.119)	(0.137)
College	-0.264***	-0.248***	-0.162*	-0.0144	-0.457*	-0.138	-0.000508	-0.0631	-0.251**
	(0.101)	(0.0882)	(0.0862)	(0.0295)	(0.248)	(0.165)	(0.111)	(0.104)	(0.102)
SR seminar	-0.303	-0.206	-0.0829	-0.0532	0.0881	-0.310	-0.0464	0.0960	0.0859
	(0.215)	(0.173)	(0.193)	(0.0593)	(0.218)	(0.215)	(0.329)	(0.326)	(0.322)
PYBT	-0.336**	-0.228	-0.209	0.0721	-0.0982	-0.135	-0.0386	-0.333**	-0.457
	(0.165)	(0.144)	(0.147)	(0.0582)	(0.264)	(0.240)	(0.184)	(0.151)	(0.288)
Family	-0.156***	-0.153***	-0.0596	-0.0134	-0.0517	-0.0174	-0.0585	-0.0646	-0.155**
	(0.0450)	(0.0403)	(0.0398)	(0.0142)	(0.0687)	(0.0507)	(0.0427)	(0.0551)	(0.0748)
Other	-0.252***	-0.236***	-0.153**	-0.0548**	-0.244*	-0.207*	-0.141*	-0.204*	-0.129
	(0.0825)	(0.0744)	(0.0705)	(0.0230)	(0.143)	(0.106)	(0.0782)	(0.115)	(0.113)
volatility		-0.614***	-0.620***	0.0126	-0.836***	-0.737***	-0.623***	-0.498***	-0.453***
		(0.0239)	(0.0241)	(0.00771)	(0.0364)	(0.0287)	(0.0306)	(0.0377)	(0.0380)
Authorised OD use		0.642***	0.625***	0.0822***	0.596***	0.576***	0.622***	0.578***	0.401***
		(0.0532)	(0.0505)	(0.0201)	(0.0920)	(0.0676)	(0.0607)	(0.0687)	(0.0859)
Extent of auth. OD use		-0.291***	-0.377***	-0.0288	-0.173	-0.105	-0.362***	-0.474***	-0.502***
		(0.103)	(0.101)	(0.0432)	(0.215)	(0.153)	(0.106)	(0.127)	(0.154)
Overdraft excess		0.101**	0.126***	-0.0382***	0.103	0.0579	0.0803	0.0754	0.213***
		(0.0428)	(0.0418)	(0.0142)	(0.0629)	(0.0488)	(0.0512)	(0.0588)	(0.0738)
OD XS duration		-0.738***	-0.614***	-0.0634*	-0.550***	-0.595***	-0.627***	-0.447***	-0.883***
		(0.115)	(0.115)	(0.0343)	(0.201)	(0.144)	(0.158)	(0.157)	(0.175)
Excess owners			0.259***		0.316***	0.253***	0.338***	0.383***	0.295***
			(0.0566)		(0.0892)	(0.0666)	(0.0642)	(0.0674)	(0.102)
Male owner(s)			0.245***		0.235***	0.329***	0.246***	0.183**	0.169*
			(0.0470)		(0.0760)	(0.0669)	(0.0612)	(0.0724)	(0.0924)
Legal form (omitted = Company)									
Partnership			-0.426***		-0.380***	-0.369***	-0.414***	-0.423***	-0.458***
			(0.0589)		(0.0968)	(0.0845)	(0.0761)	(0.0745)	(0.119)
Sole trader			-0.809***		-0.717***	-0.737***	-0.803***	-0.840***	-0.918***
			(0.0448)		(0.0657)	(0.0523)	(0.0515)	(0.0599)	(0.0890)
Industry dummies	no	no	yes	yes	yes	yes	yes	yes	yes
Region dummies	no	no	yes	yes	yes	yes	yes	yes	yes
Constant	-1.005***	-0.132	0.709***	0.0307	0.151	0.181	0.621**	1.185***	1.700***
	(0.0991)	(0.0955)	(0.195)	(0.0680)	(0.455)	(0.235)	(0.254)	(0.265)	(0.249)
Observations	5,184	5,184	4,858	4,858	4,858	4,858	4,858	4,858	4,858
(Pseudo)-R2	0.087	0.277	0.371	0.0083	0.259	0.248	0.223	0.206	0.199

6.2 Quantile treatment effects

Our analysis of treatment effects of business experience on start-up size begins by looking at some treatment effects obtained through propensity score matching and multidimensional nearest-neighbor matching. Table 5 shows these estimated treatment effects. These estimates, obtained using different matching algorithms, are highly significant and similar in magnitude. They clearly show that, on average, prior business experience is associated with a larger start-up size.

With regards to interpreting the magnitudes of these estimates, we refer to propensity score estimates (not reported in detail here) where the outcome variable is start-up size rather than relative start-up size. In this case, the ATT is 0.392 (*t*-stat = 7.27). The ATT of 0.392 corresponds to the difference between the average *log* start-up size of the treatment group (10.744) and the control group (10.354). In other words, personal prior business experience moves the average start-up size from £31,365 to £46,405. Taking exp(0.392)-1 = 0.479, we therefore find that personal prior business experience leads to a start-up size that is 47.9% larger.

Table 5: Matching estimates – Average Treatment effect on the Treated (ATT) obtained by propensity score matching (Leuven and Sianesi, 2003), and Sample Average Treatment Effect (SATE) obtained from Nearest Neighbour matching à la Abadie et al. (2004).

ATT	Std Error	t-stat
0.384	0.0534	7.19
SATE	Std Error	z-stat
0.467	0.048	9.80

NOTES: matching covariates are age, education dummies, volatility, use and extent of overdraft use (both authorized and unauthorized), dummy for excess number of owners, dummy for male owner(s), sources of advice dummies, legal form dummies, industry dummies, and region dummies.

Table 6: Quantile treatment effect estimates, and z-statistics, of the effect of prior business experience on start-up size.

Start-up size: Turnover over first year		
	QTE Coeff.	z-stat
10%	**0.291**	2.91
25%	**0.329**	4.02
50%	**0.360**	4.85
75%	**0.303**	3.40
90%	**0.430**	4.06
Start-up size: Turnover over first two years		
	QTE Coeff.	z-stat
10%	**0.455**	2.98
25%	**0.342**	3.89
50%	**0.267**	2.85
75%	**0.281**	2.77
90%	**0.416**	3.83

NOTES: matching covariates are age, education, volatility, use and extent of overdraft use (both authorized and unauthorized), dummy for excess number of owners, dummy for male owner(s), sources of advice dummies, legal form dummies, industry dummies, and region dummies.

Table 6 contains quantile estimates of the impact of prior business experience on start-up size, using quantile treatment effects. The top panel of Table 6 measures start-up size in the first year, while the lower panel of Table 6 takes an alternative measure of start-up size – total turnover over the first two years. Our QTE estimates complement our previous quantile regression estimates by confirming that business experience has a positive effect on start-up size. At all quantiles the effect is positive and significant.

Table 7: IVQTE estimates, and z-statistics, of the effect of prior business experience on start-up size. Prior business experience is instrumented by parental business experience.

Start-up size: Turnover over first year		
	IVQTE Coeff.	z-stat
10%	0.546	0.75
25%	0.912	0.60
50%	1.325	1.71
75%	**1.284**	3.62
90%	**1.156**	2.59
Start-up size: Turnover over first two years		
	IVQTE Coeff.	z-stat
10%	1.081	0.36
25%	1.763	1.72
50%	1.261	1.87
75%	**1.046**	2.21
90%	1.067	1.48

NOTES: matching covariates are age, education, volatility, use and extent of overdraft use (both authorized and unauthorized), dummy for excess number of owners, dummy for male owner(s), sources of advice dummies, legal form dummies, industry dummies, and region dummies.

6.3 Instrumental Variable QTE

We complement our baseline QTE estimates with Instrumental Variables estimation, which can help control for simultaneity in terms of factors that might be driving both start-up size and prior business experience. Since we cannot rule out the possibility that the treatment and control group differ in terms of unobservables that might affect start-up size, we therefore apply instrumental variables techniques (Oosterbeek et al., 2010). IV estimation can also help alleviate concerns of measurement error. We instrument prior business experience by the business experience of the parents, in line with previous work.[15] IVQTE requires that the instrumental variable be binary (Frolich and Melly 2008, 2010), which is satisfied in our case. Furthermore, there are four key assumptions regarding the instrument that are discussed in Frolich and Melly (2008, p10):

1) the existence of compliers: at least some individuals have accumulated business experience because their parents started a business;
2) monotonicity: the effect of having parents who started a business will weakly increase the probability of having prior business experience;
3) independent instrument: that parental business experience does not affect the start-up size of individuals directly and that individuals do not differ from each other purely on the basis of their parents;

[15] Previous studies that take parental characteristics as an instrument for entrepreneur's characteristics include Dahl and Sorenson (2012).

4) common support: the distribution of entrepreneur's characteristics is comparable independent of whether their parents had previous business experience.

Support for the externality of our instrument seems reasonable in our context, in the sense that parental business experience is not likely to be affected by the child's business experience or start-up size. Support for assumption 1) can be found in Levie (2009, p17), who observes that "those with no entrepreneurial intentions are half as likely to know a recent start-up entrepreneur" (see also Davidsson and Honig, 2003). Furthermore, Fairlie and Robb (2007, p312) observe that "the probability of business ownership is substantially higher among the children of business owners than among the children of non-business owners." Laspita et al. (2012) and Chlosta et al. (2012) offer further evidence on the intergenerational transmission of entrepreneurial intentions. Assumption 3) however is more problematic, because parents may provide their children with assets and resources, or with easier access to capital, or at the very least with tacit entrepreneurship experience that enables them to enter at a larger scale. However, we will also investigate whether there is support for these four assumptions later on in econometric terms, in recognition of the fact that a variable that is merely 'external' is not necessarily exogenous (Deaton, 2010).

Table 7 contains our IVQTE estimates, where start-up size is allowed to be endogenous, and so personal business experience is instrumented by parental business experience. A first question concerns whether our instrumental variable is an appropriate instrument. At face value, it seems reasonable to consider that parental characteristics are 'external' and hence suitable instruments for the entrepreneur's characteristics, because parental characteristics have an influence on the entrepreneur's characteristics, but are not influenced by these latter.

To test the strength of our instrument, we investigate whether parental business experience is significantly correlated with an individual's prior business experience. The naïve tetrachoric correlation between these two is highly significant at 0.1814 (p-value<0.0001, for the 6247 observations for year 1). A probit regression of personal business experience on parental business experience returns a highly significant coefficient on parental business experience of 0.2956 (SE = 0.0347; z-stat = 8.51, p<0.001). An OLS linear probability model (LPM) of the same regression model returns an F-statistic of 74.29, far above the oft-cited threshold of 10.00 (cf Staiger and Stock, 1997). We therefore take this as evidence of the relevance of our instrument.

However, the four assumptions presented in Section 4 are not all satisfied, because our regression estimates in Table 4 show that parental business experience is positively associated with start-up size even after controlling for personal business experience (which invalidates assumption 3). Therefore, parental experience is not fully exogenous because it has a direct effect on children's start-up size. Indeed, finding suitable instruments is not an easy task, and in this paper we do not claim that our instrumental variable irrefutably establishes a causal link. However, we consider it to be a meaningful complement to our baseline results. In any case, we can expect that it is more exogenous than the variable it is instrumenting (that is, personal business experience).[16]

[16]For a similar line of reasoning, see e.g. Cassiman and Veugelers, (2002, p1174).

Our IVQTE estimates display the same signs as our QTE estimates, and in terms of magnitude are much larger, although the coefficients are poorly determined in most of the cases. When we estimate the direct effect of prior business experience on start-up size, by using parental business experience as an instrumental variable, our estimates of the effects of prior business experience become much larger. Nevertheless, we must remind the reader to be especially cautious about our IVQTE estimates, because of concerns about the validity of the instrument. A conservative approach would be to focus on our QTE results in Table 6, which are all lower in magnitude (and generally more precisely determined).

7. Conclusion

Some (but not all) studies have suggested that prior business experience helps firms perform better in terms of survival. This could be due to entrepreneurial learning. Politis (2005, p403) suggests that "entrepreneurs with prior start-up experience have developed an 'entrepreneurial mind set' that drives them to seek and pursue entrepreneurial opportunities with enormous discipline, and hence, can be expected to pursue only the very best opportunities."

However, our view of empirical research using large-sample datasets is that the link between post-entry performance and entrepreneurial experience is unclear. In this paper, we suggest that entrepreneurs do not learn how to better play the game, but instead improve their chances of staying on at the 'gambling table' by starting with a larger initial stock of 'gambling chips.'

Using data from a cohort of 6247 entrepreneurs starting in 2004 and tracking their performance by looking at their bank account activity, we observe that prior business experience is associated with a significantly larger start-up size. The proportional increase in start-up size remains roughly constant across the quantiles of the distribution of start-up size. Prior personal business experience leads to an increase in expected start-up size of about 48%. IVQTE estimates (using parental experience as an instrument for personal experience) provide larger estimates of the effect of business experience on start-up size, although this instrument has its drawbacks. Other factors are significantly associated with start-up size, most notably bank account variables (e.g. use of overdraft) and also age, (university-level) education, and some sources of advice.

Building on a theoretical framework of firm growth being well-approximated by a random process, we suggested that prior business experience might lead entrepreneurs to start their subsequent businesses at a larger scale – the analogy being that of a lottery player who has not learnt how to better play the game, but increases her chances of winning by buying more tickets next time around. We found support for our Hypothesis 1, because prior business experience led to higher start-up size. However, we did not find support for our Hypotheses 2a and 2b, because the larger size of subsequent start-ups remains about the same – in terms of proportionate increase – across the start-up size distribution. We were therefore led to reject Hypotheses 2a (which posited a more-than-proportional increase in start-up size at the upper end of the distribution), and 2b (which posited that, at the lower end of the distribution, entrepreneurs might prefer to start again smaller in order to limit their downside risks).

Some limitations of our work should be acknowledged. It is not clear how our findings for UK entrepreneurs can be applied to other countries and institutional contexts. Furthermore, we focus on the first year of a cohort that started trading in the same quarter in 2004 (that is, a few years before the 2008 recession), and it may be the case that start-up conditions in a recessionary period are different.

Further work could explore how start-up size may be a reference point that can be taken as a proxy for aspiration level or reservation wage of the founding entrepreneur(s). It may well be that firms that start large but shrink in the years after entry are much more likely to exit than firms that start small but grow in the years after entry (Coad et al., 2013). We would also welcome further work that analyzes large-sample, representative, datasets to identify which aspects of business performance are enhanced by prior business experience. Future work could also investigate prior employment history in more depth, exploiting information on the duration of previous entrepreneurial experience, the degree of relatedness of their prior industry experience, and their unemployment history (to distinguish necessity entrepreneurs from opportunity entrepreneurs).

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Appendix

Table A1: Variables description

Start-up size	Log of sales in the first year (to be precise, log of credit turnover, in GBP).
Age	(mean) age of start-up owner-manager(s)
Age squared	quadratic function of age, calculated as (age-mean(age))2 to avoid problems of multicollinearity
Education	highest educational attainment of owner-manager(s): none (=1), GCSE (=2), A-level (=3), Degree or higher (=4), according to the UK National Vocational Qualication scale.
Business experience (self)	The individual has prior business experience
Business experience (parental)	Prior business experience is possessed by the individual's parents
Sources of advice	sources of advice and support sought prior to start up: enterprise agency/business link (EABL), accountant, solicitor, college, Barclays `Start Right' seminar, the Prince's Youth Business Trust (PYBT), family, and other (recoded into dummy variables)
No. owners	Number of owners
Male owner(s)	= 1 if there is at least one male owner-manager of the start-up, 0 otherwise
Legal form	legal form of start-up, recoded into dummy variables: partnership (=2) or sole trader (=3). Omitted category is Company legal form (including LLP).
Volatility	ratio of the standard deviation of monthly turnover to the mean monthly turnover, summed over two six-month periods to obtain an annual volatility indicator
Overdraft excess	= 1 if in excess of authorised overdraft limit at any time
OD XS duration	proportion of period in excess of authorised overdraft limit
Authorized OD use	= 1 if authorised overdraft used at any time
Extent of auth. OD	use mean proportion of authorised overdraft limit used
Industry	business sector of firm at start-up, recoded into dummy variables: Agriculture; Manufacturing; Construction; Motor trades; Wholesale; Retail; Hotels & catering; Transport; Property services; Business services; Health, education & social work (HESW); and Other services
Region	1 = East of England, 2 = East Midlands, 3 = London, 4 = North East, 5 = North West, 6 = South East, 7 = South West, 8 = West Midlands, 9 = Yorkshire, 10 = Scotland, 11 = Wales, 12 = Northern Ireland